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Drivers of Complexity in Humanitarian Operations

4 December 2013

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14. ABSTRACT
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Abstract

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Keywords: Humanitarian assistance, disaster relief, disaster response, Federal Emergency Management Agency, Centre for Research on the Epidemiology of Disasters, Emergency Events Database

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List of Acronyms and Abbreviations

C2	Command and Control
CRED	Centre for Research on the Epidemiology of Disasters
DoD	Department of Defense
DR	Disaster Relief
EM-DAT	Emergency Events Database
FEMA	Federal Emergency Management Agency
HA	Humanitarian Assistance
HADR	Humanitarian Assistance/Disaster Relief
NGO	Nongovernmental Organization
USAID	U.S. Agency for International Development

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I. INTRODUCTION

A. BACKGROUND

Planning for humanitarian assistance is extremely challenging because of the uncertainty in predicting when a disaster is going to occur, where it is going to happen, and how catastrophic it will be. Knowing the exact disaster scenario would be ideal but is simply not realistic. A significant percentage of the world's population has suffered as the result of both human (man-made) and natural disasters in recent years. The goal of this report is to determine whether personnel affected, number of casualties, and total damage costs are related to the operational complexity of the humanitarian response, based on the geographical dispersion and the speed of onset of natural disasters.

The trend of reported natural disasters for the past 35 years has been steadily increasing, as seen in Figure 1 (Emergency Events Database [EM-DAT], 2013). One of the causes of this increased trend is an increasing world population, especially toward more coastal regions, and an increase in reporting smaller disasters. As populations grow, so do the number of reported natural disasters. The unique challenges posed by natural disasters, combined with their increased frequency, underscore the importance of conducting research in this area.

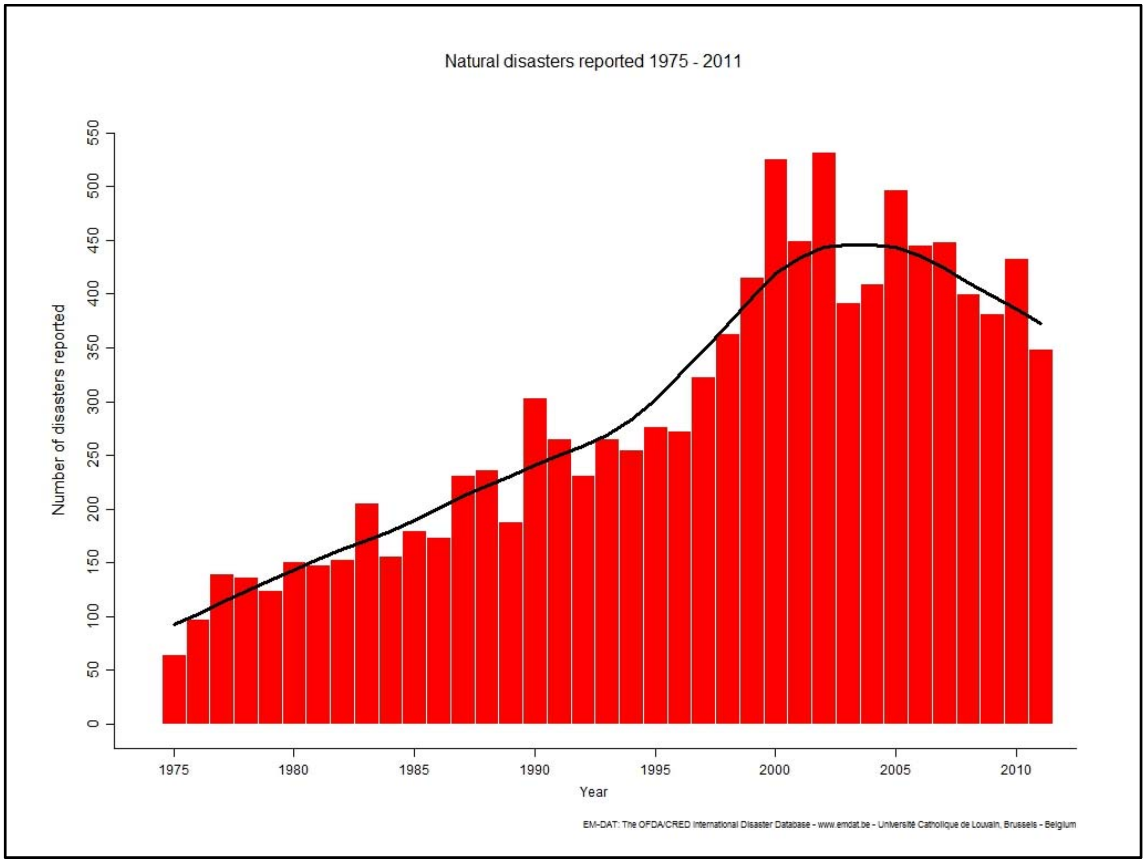

Figure 1. Natural Disasters 1975–2011
(EM-DAT, 2013)

B. RESEARCH MOTIVATION AND QUESTIONS

One would suspect that increases in geographical dispersion and speed of a disaster would drive an increase in the complexity of relief operations. The goal of this study is to analyze historical disaster information to ascertain the validity of this suspected relationship.

Determining whether the operational complexity of humanitarian assistance/disaster relief (HADR) operations relates to the dispersion of geographical area affected and the speed of onset of natural disasters can provide valuable information to planners of all agencies. Although positive results from this project may be useful in planning and conducting HADR, this project has limitations in its scope.

The main limitation of the project is the fidelity of the forecast of when or where a disaster will occur or how catastrophic it will be. This limitation applies not only to this project but also to almost any planning efforts conducted for HADR. Without the ability to forecast where or when a disaster may occur, it is difficult to predict the assets and supplies that may be needed during recovery efforts.

The lack of information on when and where a disaster may strike adds levels of difficulty to budget and resource planning, which affects the many agencies involved in HADR. To appropriately determine the level of difficulty within the classifications outlined in Figure 2, we first have to establish parameters by defining the location: localized or dispersed (Apte, 2009).

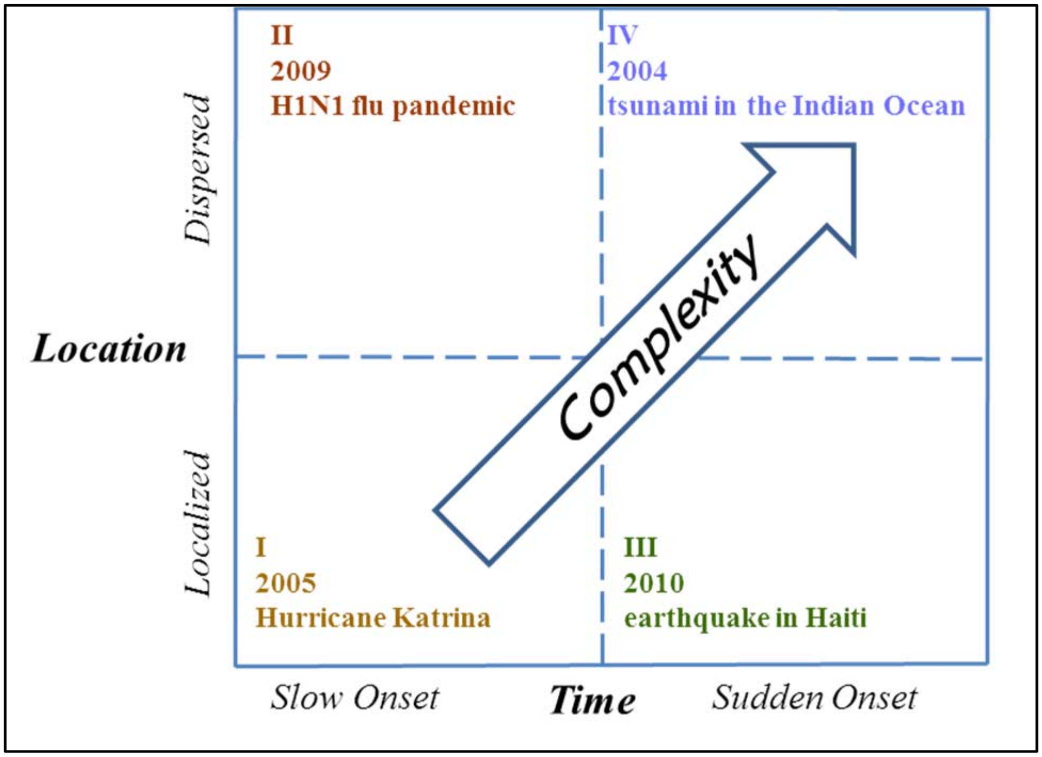

Figure 2. Disaster Classification and Difficulty of Response
(Adapted from Apte, 2009)

The conclusion we derived from our project is intended to provide analysis parameters to assist response planners and financial providers in better determining the complexity associated with a disaster, given its speed of onset and dispersion.

C. SUMMARY OF METHODOLOGY

Using the Emergency Events Database (EM-DAT) available from the Centre for Research on the Epidemiology of Disasters (CRED), we collected and filtered the following information on 281 U.S. disasters that occurred between 2000 and 2011:

- year,
- sequence number,
- disaster subgroup,
- disaster type,

- disaster subtype,
- example,
- entry criteria,
- region,
- location,
- disaster duration,
- number killed,
- number affected, and
- total damage.

We utilized data from the U.S. Census Bureau (n.d.) to supplement the EM-DAT information to determine the area affected for each disaster. We then ranked each disaster and assigned a value to represent the speed of onset based on each type and subtype. Plotting the disasters yielded a graph that we further analyzed to determine whether any patterns existed by comparing the number of personnel affected, number of personnel killed (referred throughout the rest of this report as "number of casualties"), and total damage costs. The goal of this analysis is to determine whether the complexity of a disaster can be determined from its dispersion and speed of onset.

D. STRUCTURE OF THE REPORT

This report is divided into five chapters. In Chapter I, we discussed the background, presented our research motivation and research questions, summarized the methodology used, and provided a layout for this report. In Chapter II, we review literature on HADR topics and how it relates to this project. In Chapter III, we identify the source of our data and the methodology used. In Chapter IV, we provide the analysis of data collected, the findings of hypothetical testing, and a discussion of the results. Finally, in Chapter V, we discuss conclusions and recommendations for further action and research.

II. LITERATURE REVIEW

A. BACKGROUND OF HUMANITARIAN ASSISTANCE/DISASTER RELIEF

1. Disasters

The term *disaster* has different meanings to different organizations and people. The U.S. Federal Emergency Management Agency (FEMA) requires the president's authority to determine the need for federal supplemental aid and uses a statutory definition from the Disaster Relief and Emergency Assistance Act (Robert T. Stafford Act, 2013), provided by U.S. Congress, to define a major disaster as follows:

> Any natural catastrophe (including any hurricane, tornado, storm, high water, wind-driven water, tidal wave, tsunami, earthquake, volcanic eruption, landslide, mudslide, snowstorm, or drought) or, regardless of cause, any fire, flood, or explosion, in any part of the United States, which, in the determination of the President, causes damage of sufficient severity and magnitude to warrant major disaster assistance under the Stafford Act to supplement the efforts and available resources of States, local governments, and disaster relief organizations in alleviating the damage, loss, hardship, or suffering caused thereby. (p. 59)

Federal disaster law restricts the use of arithmetical formulas or other objective standards as the sole basis for determining whether to provide federal supplemental aid in response to a disaster event. As a result, FEMA assesses a multitude of factors when determining the severity, magnitude, and impact of a disaster event (FEMA, 2013). The following are some of the primary factors that FEMA (2013) uses to assess disaster events:

- amount and type of damage (number of homes destroyed or with major damage);
- impact on the infrastructure of affected areas or critical facilities;
- imminent threats to public health and safety;
- impacts to essential government services and functions;
- unique capability of the federal government;
- dispersion or concentration of damage;
- level of insurance coverage in place for homeowners and public facilities;

- available assistance from other sources (federal, state, local, voluntary organizations);
- state and local resource commitments from previous, undeclared events; and
- frequency of disaster events over a recent time period.

Since 1988, the CRED has maintained the EM-DAT. The CRED's website states that "the main objective of the database is to serve the interest of the humanitarian action at national and international levels" (EM-DAT, 2013). Just like FEMA, the CRED requires that disasters meet certain criteria in order for them to be recorded within its database:

- 10 or more people reported killed;
- 100 or more people reported affected;
- declaration of a state of emergency; and
- call for international assistance (EM-DAT, 2013).

2. Humanitarian Assistance and Disaster Relief

The terms *humanitarian assistance* (HA) and *disaster relief* (DR) both include operations designed to relieve suffering due to the occurrence of a disaster and to aid in recovery (Greenfield & Ingram, 2011). There is a difference between the two terms, however. Various academic literature suggests that DR is defined by its immediacy, whereas HA is the provision of more long-term support to help alleviate suffering and aid in recovery (Apte, 2009; Kovács & Spens, 2007; Tomasini & Van Wassenhove, 2009b).

The Department of Defense (DoD) also defines HA and DR in Joint Publication 1-02 by the Chairman of the Joint Chiefs of Staff:

> **Humanitarian Assistance—**Programs conducted to relieve or reduce the results of natural or manmade disasters or other endemic conditions such as human pain, disease, hunger, or privation that might present a serious threat to life or that can result in great damage to or loss of property. Humanitarian assistance provided by US forces is limited in scope and duration. The assistance provided is designed to supplement or complement the efforts of the host nation civil authorities or agencies that may have the primary responsibility for providing humanitarian assistance. (Gortney, 2010, p. 127)
>
> **Foreign Disaster Relief—**Prompt aid that can be used to alleviate the suffering of foreign disaster victims. Normally it includes humanitarian services and transportation; the provision of food, clothing, medicine, beds, and bedding; temporary shelter and housing; the furnishing of

medical materiel and medical and technical personnel; and making repairs to essential services. (Gortney, 2010, p. 127)

3. Humanitarian Assistance/Disaster Relief Life Cycle

Kovács and Spens (2007) identified the three phases of disaster management by stating, “Different operations can be distinguished in the times before a disaster strikes (the preparation phase), instantly after a disaster (the immediate response phase) and in the aftermath of a natural disaster (the reconstruction phase)” (p. 220), as illustrated in Figure 3. Each of these phases of the HADR life cycle requires different resources and expertise because of the different requirements.

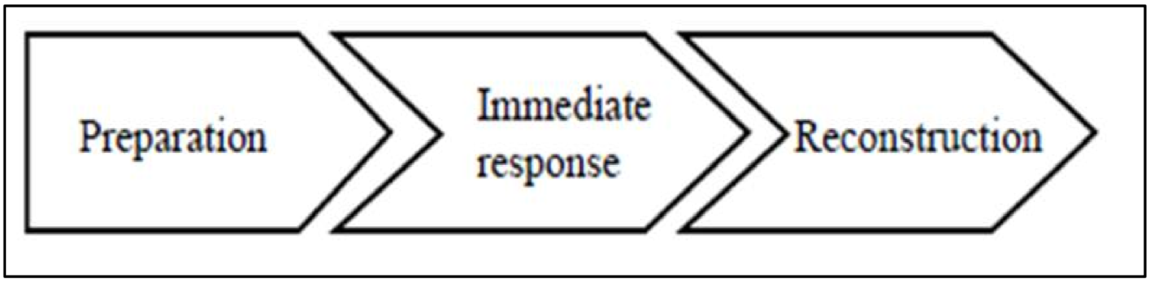

Figure 3. Phases of Disaster Relief Operations
(Kovács & Spens, 2007)

Tatham and Houghton (2011) illustrated the disaster management cycle shown in Figure 4. Rather than describe the HADR phases as preparation, immediate response, and reconstruction, Tatham and Houghton (2011) described the phases as prevention, transition, and recovery. Figure 4 shows the different events that occur within each phase of the HADR cycle in more detail.

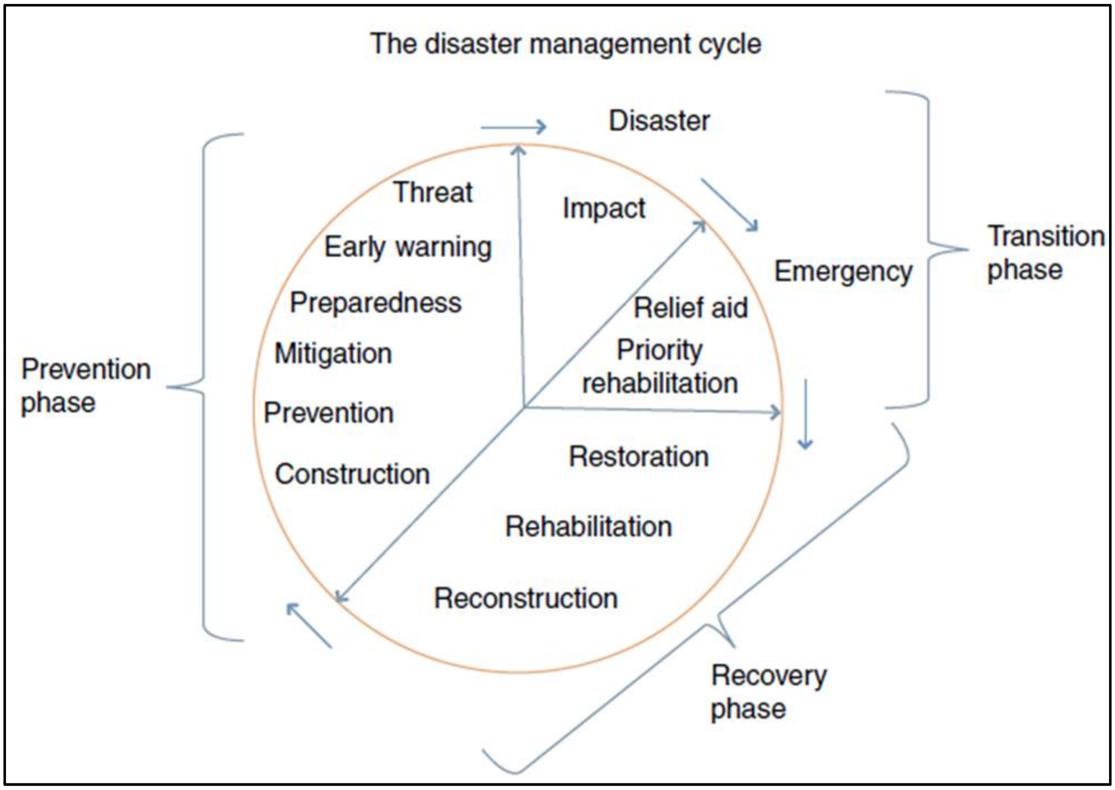

Figure 4. The Disaster Management Cycle
(Tatham & Houghton, 2011)

Transportation planning is a very important part of the immediate response phase to a disaster because, since the 1990s, it has grown to be the second largest operating cost in HADR, behind disaster relief personnel (Pedraza Martinez, Stapleton, & Van Wassenhove, 2011).

4. Disaster Classification

Although FEMA's definition of a disaster defines the outcome, it does not define the nature of the event. Van Wassenhove (2006) further classified disasters according to their speed (slow versus sudden onset) and their source (natural versus man-made). His classification structure is useful because it describes some of the challenges that occur when providing HA and DR. Figure 5 shows Van Wassenhove's (2006) explanation of disasters.

	Natural	Man-made
Sudden-onset	Earthquake Hurricane Tornadoes	Terrorist Attack Coup d'Etat Chemical leak
Slow-onset	Famine Drought Poverty	Political Crisis Refugee Crisis

Figure 5. Explaining Disasters
(Van Wassenhove, 2006)

Ergun, Karakus, Keskinocak, Swann, and Villarreal (2010) also grouped disasters into these two categories (natural and man-made), but they also explained that disasters could further be "categorized by predictable timing (or seasonal) such as floods or unpredictable timing like earthquakes and predictable location such as hurricanes or unpredictable locations like tsunamis" (Ergun et al., 2010).

Apte (2009) classified disasters into four groups, as seen in Figure 2: slow-onset/localized, slow-onset/dispersed, sudden-onset/localized, and sudden-onset/dispersed. Disasters that occur over time and are slow-onset allow responders to plan and prepare relief efforts. Disasters that strike suddenly pose a more significant challenge for responders because these types of events are difficult to plan for in advance. The level of difficulty of response or relief is also different for disasters that affect localized areas as opposed to large and populated geographical areas. Localized, slow-onset disasters are on one end of the spectrum on the level of difficulty, while dispersed, sudden-onset disasters are on the other end of the spectrum (Apte, 2009).

The causes of disasters are not always clear-cut, so just the process of classifying the disasters can be a challenge (Kovács & Spens, 2009). Floods, for example, can be considered *natural* due to a heavier-than-normal rainy season, *man-made* as a result of dams being constructed on earthquake-prone tectonic fault lines, or *primarily natural* but with a man-made component, because deforestation resulted in the flooding disaster. Many disasters defy a clear-cut categorization. This issue is one of the challenges in humanitarian logistics, since man-made causes of

disasters can be counteracted, thus altering the focus of relief programs (Kovács & Spens, 2009).

To understand the relationship between disaster classification and operational complexity, we began by looking at several projects undertaken by other researchers in which classification was utilized based on the quadrants of Apte (2009), shown in Figure 2. A common theme that we identified among these classifications is the need for further research regarding the parameters that define localized versus dispersed, and slow-onset versus sudden.

Yoho and Apte (2011) found that while disasters were classified into the four quadrants, the terms *slow-onset*, *sudden-onset*, *localized*, and *dispersed* were relative. Determining the accuracy of the localized or dispersed categorization of disasters is important; however, the way a disaster is categorized might vary depending on the lens through which a person views the disaster. From a global perspective, a disaster that occurs in a single country could be considered a localized incident. At the same time, a disaster in a single region within a larger country—such as a state within the United States—could also be viewed as a localized incident. By acknowledging the perspective from which one looks, the relative impact of a disaster changes. It is natural to infer that a dispersed disaster is one that impacts multiple countries in the world or multiple states within a single country. Many previous studies have used a worldwide view to classify the Indonesian tsunami of 2004, the Haiti earthquake of 2010, and the Tohoku earthquake and tsunami of 2011.

We found that the labels *localized* and *dispersed* varied depending on the lens through which the disaster was viewed. Viewing from a countries perspective, we could consider a disaster dispersed due to the affected land area and personnel, but viewed from a global perspective, we could consider the disaster localized. For example, Ures (2011) classified the Haiti earthquake in 2010, claiming 230,000 lives and displacing two million people, as localized and sudden-onset. For comparison purposes, Ures (2011) classified the Indonesian tsunami of 2004 as dispersed and sudden-onset due to its impact spanning 14 countries, even though it claimed just over 227,000 lives and displaced 1.1 million people. Additionally, Yoho and Apte (2011) chose to classify the Haiti earthquake in the same manner as Ures (2011) did and explained their reasoning by choosing to define *localized* and *dispersed* based on the number of civil administrative districts impacted. They elaborated on this definition by explaining that districts can be defined by cities, countries, townships, parishes, provinces, or states. Although geographic impact is one way to differentiate between localized and dispersed, there are many other factors to consider, and this shifting classification provides the need for further research. Geographic distances do increase the logistical problems, but it is still unclear as to

whether an increase in population density over a smaller landscape requires an increase in the volume of resources (e.g., recovery personnel and equipment) equal to that of a dispersed-impact disaster with low density.

B. COMPLEXITIES OF HUMANITARIAN ASSISTANCE/DISASTER RELIEF LOGISTICS

Although researchers have not settled on a single definition for humanitarian logistics, Thomas and Mizushima (2005) agreed, after much deliberation, on the preliminary definition as "the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from point of origin to point of consumption for the purpose of meeting the end beneficiary's requirement" (p. 60). There are complexity barriers in every facet of humanitarian logistics that impact relief operations. These complexities fall into three general groups: governance, leadership, and logistics.

1. Governance

The construct of the host nation's governing body, cultural ideologies, judicial laws, economic stability, and infrastructure can create significant barriers to the efficient execution of relief efforts. Each of these evaluators can either enhance or degrade an area's ability to withstand a natural disaster.

The bureaucratic structure of U.S. emergency management operations is a good place to analyze the impact of laws on relief operations. Takeda and Helms (2006) studied the events surrounding the federal response to Hurricane Katrina in 2005 and described FEMA's role as "the governmental body dedicated to protecting and aiding Americans in the case of natural and man-made disasters" (p. 398). They also noted that after the events on 9/11, the United States transferred the majority of FEMA's resources to the Emergency Preparedness and Response Directorate under the supervision of the newly created Department of Homeland Security.

Relief funds that are scrutinized by multiple levels of the government to ensure fair distribution delay swift responses in the aftermath of a disaster. Takeda and Helms (2006) described bureaucratic management systems as complicated, consisting of numerous experts working in very specific fields, requiring many meetings and sharing of information, to facilitate the centralized decision-making. They found that the bureaucratic model has one universal problem that is detrimental to the success of relief operations. Decentralized knowledge with centralized decision-making "are barriers to swift analysis and implementation of 'outside' information and resources, making it difficult to respond quickly and efficiently in the aftermath of hurricanes" (Takeda & Helms, 2006, p. 402). These roadblocks are a common theme among responses to all disasters and significantly

increase the complexity of operations by preventing rapid relief efforts by responders.

Governance issues come in many forms. Countries ranking high in governance tend to provide better infrastructure, especially in terms of disaster preparation. For example, a country investing resources to build improved seawalls and enforce stricter building codes helps to minimize damages resulting from an earthquake or tsunami. Although not all improvements will prevent severe damage, devastation can be much worse if a government does not prioritize the investment of federal funds in this preparation. Ergun et al. (2010) noted that the "Indian government did not invite international aid agencies to participate at all in the first 60 days of the relief effort" following the 2004 Indonesian tsunami. This type of governmental response contributes to the complexity of HADR as well. Haiti had very little invested in preparing its infrastructure to handle a disaster such as the earthquake in 2010 and the resulting damage, which included "28 of 29 government ministry buildings in the capital, killing 17 percent of the country's civil service and destroying decades of administrative records … and decimation of national government"; the nature of these impacts increased the complexity of operations immensely (Ures, 2011, p. 7).

2. Leadership

Disaster relief operations are very similar to those found in combat situations in which a lack of leadership can make a mission misguided and ineffective. Mission focus and organization become more complex with each additional unit, task, or layer of decision-makers and can lead to confusion when coordinating unified relief efforts. Deficiencies in the command and control (C2), specifically lines of communication, burden all facets of relief operations. Gabriel (2012) noted that communication issues proved to increase the complexity of operations in support of Hurricane Katrina in 2005, Cyclone Nargis in 2008, and the Haiti earthquake in 2010. Additionally, Gabriel (2012) discovered that the "sharing of information is particularly critical following a disaster because no responding entity can be the source of all the necessary information" (p. 16).

Following a disaster, a myriad of supporting cast members arrive on scene and fall into one of the many categories shown in Figure 6. Although the leadership and direction should start with the host nation, many times, the host nation itself is affected by the disaster or is not prepared to command such a large-scale operation. Tomasini and Van Wassenhove (2009a) highlighted this complexity when they described actors with little reason to work together prior to the disaster who are then faced with the challenge "to combine all their capacity and capability to relieve human suffering" (p. 549). Demand for leadership under these circumstances initially leads to the inefficient utilization of resources. Herbert, Prosser, and Wharton (2012)

noted that when when the United States is involved in operations, there is a distinct flow of information in which the military typically takes over on-site unless the U.S. Agency for International Development (USAID), a nongovernmental organization (NGO), is available and in a position to do so.

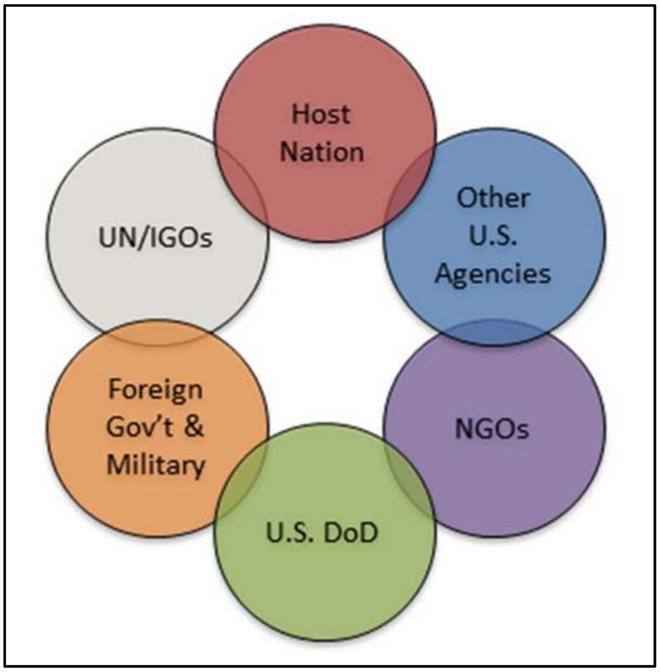

Figure 6. Typical Organizations Involved in HADR Missions
(Gabriel, 2012)

Wishart (2008) interviewed 34 individuals within the military, NGOs, the United Nations, and the U.S. government to facilitate an understanding of how to build collaborative capacity in the initial stages of relief operations. He found significant barriers due to cultural differences among organizations, especially where the military was involved. The nature of military operations does not fully translate to the civilian sector and can intimidate or subdue immediate collaborative efforts among the involved entities. Wishart (2008) found that 91% of the respondents noted organizational distrust between groups, and 50% stated that this distrust was a barrier to collaborative effort, while 53% claimed that cultural differences were a barrier to collaboration. In addition to C2 difficulties, the clashing of cultures and trust barriers among responders were contributors to the complexity of relief operations (Wishart, 2008).

3. Logistics

Relief personnel are the central node to providing support after a natural disaster, and without them, host nations, states, or cities could not receive the necessary supplies to both survive the initial response and begin reconstruction.

Several works note that the logistics of providing supplies to the affected area are both costly and difficult. Oloruntoba and Gray (2006) stated, “International humanitarian supply chains are clearly unpredictable, turbulent, and requiring flexibility” (p. 117). These defining characteristics were supplemented by Ergun et al. (2010), who stated that the “demand structure of disasters is complicated and challenging because of the high unpredictability of its three main dimensions: time, location, and magnitude” (p. 5). Our review of multiple articles revealed a common theme among researchers attempting to discover solutions to the many challenges of humanitarian supply chains. In the literature we reviewed, the common method of analysis was to compare humanitarian supply chains to regular (commercial or for-profit) supply chains.

The most common logistical challenges to humanitarian supply chains can be grouped in the following categories: complex environment, customer, unsolicited donations, speed, and professional expertise, which are presented in no particular order.

a. Complex Environment

The operating environment in a natural disaster poses a significant challenge to logisticians trying to get vital supplies to those who need them because of destabilized infrastructure, such as blocked roadways and downed communications. Less developed regions are also more prone to a larger scale destruction of their infrastructures due to poor housing situations and inadequate construction requirements (Kovács & Spens, 2007). The added pressures of a limited time frame can mean the difference between life and death, a consequence that is oftentimes not dealt with in the private sector.

b. Customer

Defining the customer of a humanitarian supply chain is challenging. Although this is easily identifiable in a commercial supply chain, the person receiving the goods of a humanitarian supply chain has little to no impact on what is being delivered or the manner in which it is delivered. Oloruntuba and Gray (2006) stated that it is actually the donor who needs to be targeted to support the humanitarian actions. Identifying the customer allows organizations to focus efforts to correct the issue of customer responsiveness to supply chain efficiency. Oloruntoba and Gray (2006) explained that the majority of donors preferred to donate tangible items or funds to purchase tangible items because donors were able to easily recognize the support that these items would provide to disaster victims; however, this leaves little to no funds for the logistics side of the supply chain, such as forklifts. Ergun et al. (2010) and Tomasini and Van Wassenhove (2009b) echoed this concern while noting the difficulties of managing the quantity and mix of donations from

participating donors who display varied levels of commitment to improving the relief efforts.

c. Unsolicited Donations

After a disaster, donations can come from many different sources and are often unsolicited. Logisticians will rarely have oversight on these donations, and this lack of visibility oftentimes creates unintended problems, especially when unnecessary supplies have to be managed. Tomasini and Van Wassenhove (2009b) discussed how unsolicited donations can add complexity to the operation, inefficiently taking up resources that could instead be used to provide better quality assistance.

d. Speed

Speed is a significant logistical challenge for humanitarian supply chains. Kovács and Spens (2007) pointed out that “the speed of humanitarian aid after a disaster depends on the ability of logisticians to procure, transport and receive supplies at the site of the humanitarian relief effort” (p. 99). Commercial supply chains are typically evaluated using indicators like cost, speed, quality, and flexibility. Tomasini & Van Wassenhove (2009b) ascertained that while the focus of supply chains can differ among industries depending on their development, humanitarian supply chains must continually prioritize speed, due to the necessity of responding to acute emergencies.

To increase the speed of responses to natural disasters, both Tomasini and Wassenhove (2009b) and Ergun et al. (2010) highlighted the need for an agile supply chain that requires the leaning out of processes that add little value. There is plenty of room for improvement, especially regarding the total lead-time of moving supplies in the humanitarian sector.

e. Professional Expertise

The lack of logistical experience among the major providers within the humanitarian supply chain is also a major complication. Both Oloruntoba and Gray (2006) and Ergun et al. (2010) described how the majority of personnel managing the supply chain for relief operations are not trained to do so and are rarely capable of resolving many of the issues that arise during the course of relief missions. Oloruntoba and Gray (2006) specifically noted in prior research that

> a survey of 45 international aid organisations found that over 80 percent of all respondent organisations had a member of staff specialising in logistics and transportation duties, but only 45 percent had someone with a formal qualification in logistics, transport or related areas. (p. 118)

Additional research conducted by Thomas and Mizushima (2005) analyzed a study conducted by the Fritz Institute detailing the lackluster performance in the logistics field surrounding humanitarian operations. They found that senior management spent all available resources procuring funds, investing in information and management systems, and engaging in emergency response planning, leaving the challenges of logistics and the training of logisticians absent in all planning stages of their response. This lack of attention leads to extreme inefficiencies and excessive spending to move resources and supplies during relief operations.

III. DATA/METHODOLOGY

Data collection is the most important and difficult part of this project because it provides differentiators to assess the difficulty of providing relief. We collected statistical data for this research from the EM-DAT International Disaster Database. The database is maintained by the CRED at the School of Public Health of the Université Catholique de Louvain located in Brussels, Belgium (EM-DAT, 2013).

The archived data set contains statistical information for every disaster reported to the CRED from the years 2000–2011. The data is organized with a numeric identifier based on the year in which the disaster occurred, and then by disaster subgroup/type/subtype, as shown in Table 1.

Table 1. EM-DAT Disaster Categorization

DISASTER SUBGROUP	DISASTER TYPE	DISASTER SUBTYPE
Biological	Epidemic	Viral Infectious Diseases
	Drought	Drought
Climatological	Extreme Temperature	Heat wave
		Cold wave
		Extreme winter conditions
		Freezing rain
	Wildfire	Bush/Brush fire
		Forest fire
		Scrub/Grassland fire
Geophysical	Earthquake (seismic activity)	Earthquake (ground shaking)
	Volcano	Volcanic eruption
Hydrological	Flood	General Flood
		Flash flood
	Mass movement wet	Landslide
		Mudslide
Meteorlogical	Storm	Extratropical cyclone (winter storm)
		Local storm
		Blizzard
		Hailstorm
		Severe storm
		Snowstorm
		Snowstorm/Blizzard
		Thunderstorm
		Tornado
		Tropical cyclone

The database contains multiple fields in which available information is recorded about each disaster. The first entry is the location, containing the country, continent, and any specific details, such as states, counties, or cities that were affected. The second entry contains the time period in which the disaster occurred, given in start month, day, and year, followed by ending month, day, and year. The

remaining three entries are the number of personnel affected, number of casualties, and total damages (in thousands US$).

A. DATA FILTERING

We filtered the data to isolate only those disasters that occurred in the United States during the date range of the provided database (2000–2011). We applied this filter to control complexity factors involving economic and political instabilities that contribute more significantly in disasters that occur outside of the United States. Choosing a first-world country ensures that a base level of preparation has been executed in the country, such as stricter building codes, better disaster preparedness, and a more capable emergency response force. Using only the United States in our sample also reduced additional opportunities for human error, since many of the locations that were entered contained spelling errors. In addition to the potential for inputting incorrect data, the time required to correct these types of spelling mistakes would have increased significantly if we had analyzed a country with which we lacked familiarity.

B. DATA PREPROCESSING

Upon filtering the database to the United States only, there were 281 disasters available for analysis. We used the U.S. Census Bureau (n.d.) website to collect 2010 census data for each location listed as an affected area for each disaster. We recorded census data regarding population size, land area in square miles, population density (persons per square mile), and median household income. We chose these categories to determine whether the complexity of operations could be linked to the number of people affected in the total population, the population density of the affected area, or the economic stability of the affected region represented by the median household income.

Once we had populated all of the information, we determined that only 259 disasters contained adequate location data to be analyzed against the speed of onset ranking for those disasters. These 259 disasters with accompanying data became the sample for our research. Although total land area could be calculated for the sampled disasters, the vagueness of the affected areas prevented us from collecting complete population density and median household income information on all 259 disasters.

C. TIME (X-AXIS VALUE)

We developed a method to plot the selected disasters in the format shown in Figure 2. Once we collected parameters on all sample disasters, we quantified the speed of onset with a numerical value for each disaster subtype utilizing a ranking method. This was accomplished by ranking the subtypes listed in Table 1 in

numerical order, with 1 being the slowest onset and 27 being the most sudden. We conducted our rankings individually and then consolidated our answers into a final system after discussing our differences. The final speed of onset results are displayed in Table 2; we agreed that a drought would be given the value of 1 as the slowest onset disaster and an earthquake the value of 27 as the most sudden onset disaster. We chose to rank these disasters so that each type had its own discrete *x* value. This allowed for better data management when conducting analysis and provided better graphical representations.

Table 2. X-Axis (Speed of Onset) Ranking

Disaster Type	Rank	Count
Drought	1	4
Epidemic	2	0
Viral Infectious Diseases	3	2
Cold Wave	4	2
Heat Wave	5	7
Extratropical Cyclone (Winter Storm)	6	1
Tropical Cyclone	7	25
Storm	8	24
Local Storm	9	2
Snowstorm	10	10
Snowstorm/Blizzard	11	12
Blizzard	12	1
Thunderstorm	13	5
Severe storm	14	4
Flood	15	4
General Flood	16	44
Freezing Rain	17	1
Hailstorm	18	3
Wildfire	19	2
Forest Fire	20	28
Bush/Brush Fire	21	1
Scrub/Grassland Fire	22	6
Flash Flood	23	5
Mudslide	24	1
Tornado	25	57
Volcanic Eruption	26	0
Earthquake (Seismic Activity)	27	4

D. LOCATION (Y-AXIS VALUE)

We determined the location to be the land area (square miles) that was recorded as the affected area of a disaster. We consolidated data collected from the U.S. Census Bureau (n.d.) for state, county, and city land area for all locations listed for each disaster. This provided a single numerical value to assist in categorizing a disaster as localized or dispersed, in accordance with Figure 2. For example, if a tornado was listed as affecting Texas and Oklahoma, then the affected area would be the sum of their respective land areas. This visual depiction provided us with an initial opportunity to observe the interactions of location and time with respect to past disasters (see Figure 7). Disaster classifications broken into their respective quadrants are shown in Figure 8.

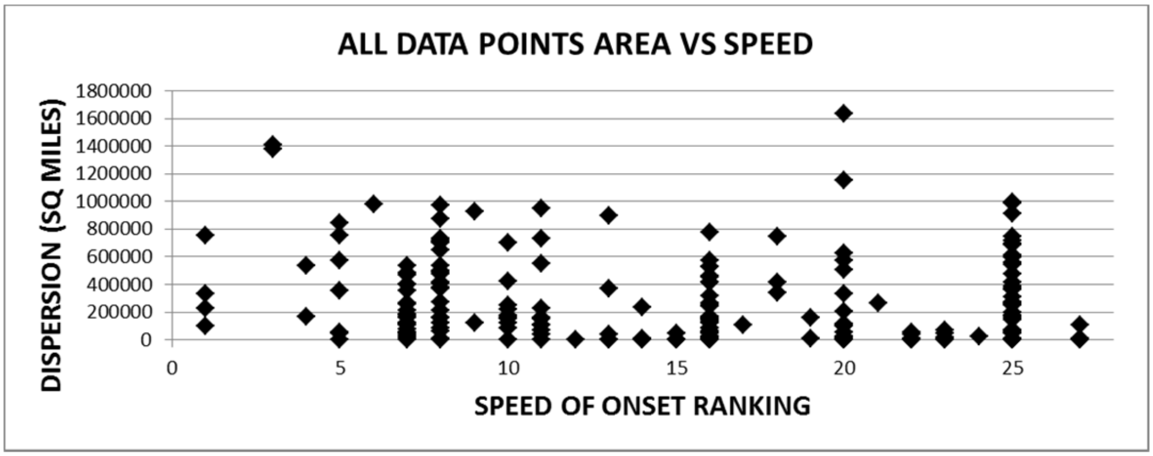

Figure 7. Disaster Classification

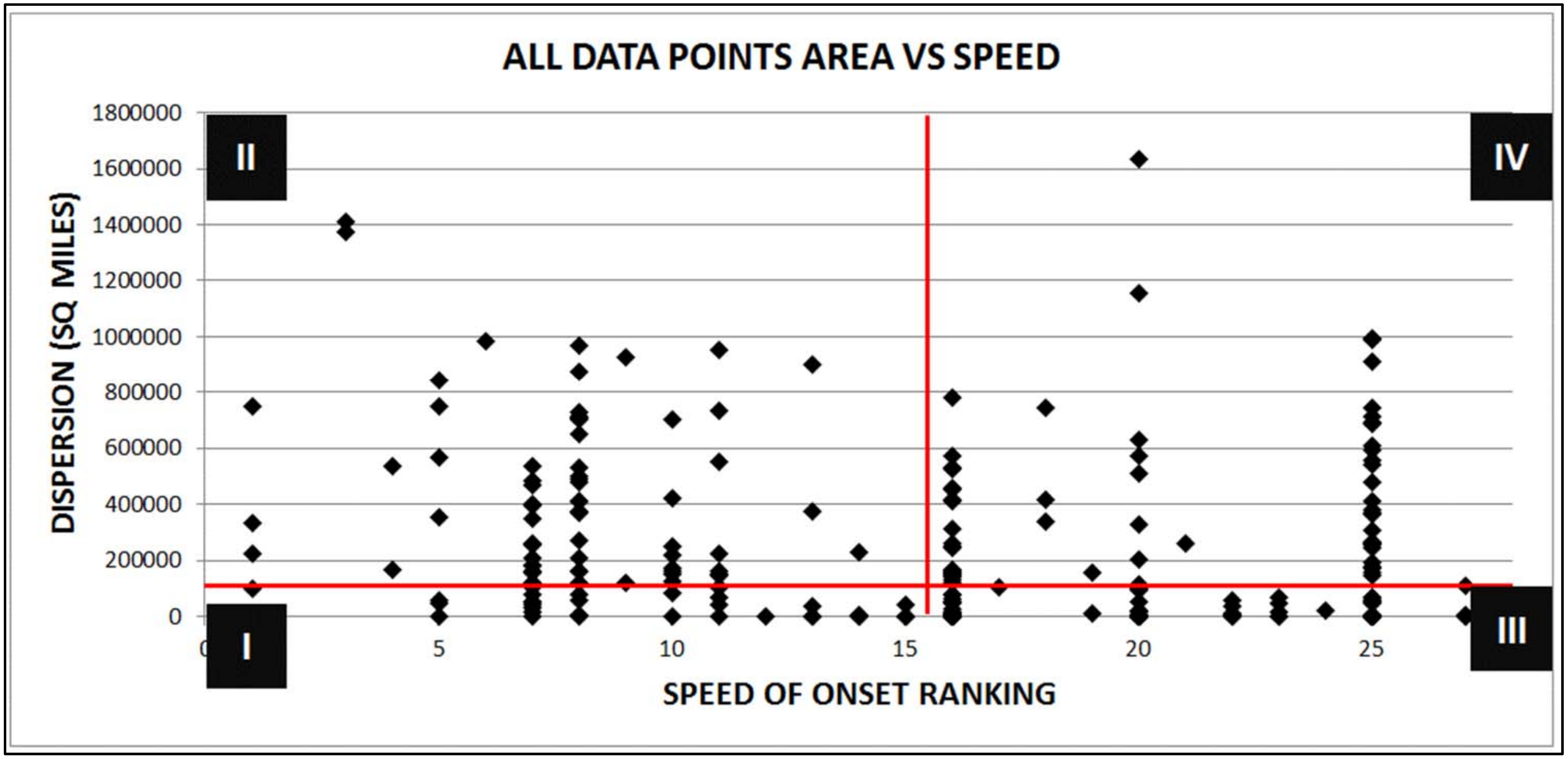

Figure 8. Disaster Classification by Quadrant

E. CLASSIFICATION

Once we plotted the sample disasters, we observed two possible outliers: 257 of the 259 disasters each had an affected area of 1.7 million square miles or fewer. The remaining two disasters each contained an affected area of more than 61 million square miles. Calculating a *z*-score for these two disasters involved measuring them against the mean of the sample group and determining whether these were typical or atypical of our data set by showing how many standard deviations away these disasters were from the sample mean.

The Empirical Rule states that approximately 68.3%, 95.5%, and 99.7% of values fall within 1, 2, and 3 standard deviations from the mean. Assuming that our population sample was normal, we identified any disaster with a *z*-score greater than 3 as an outlier. Using this method revealed *z*-score results of 11.55 and 11.52, respectively, for these two disasters. Although there were casualties in each disaster and only one included a list of damages, we decided that the affected locations provided were too vast to be calculated properly. The locations listed for these two outlying disasters were the Midwest, Southeast, Northeast, and Plains areas of the U.S.

Removing the outliers provided clarity among the remaining data points. To categorize the remaining disasters into the appropriate quadrant, we calculated both the mean and median of the *x* and *y* values. The results are provided in Table 3.

Table 3. Mean/Median for *x* and y Values

	SPEED OF ONSET RANKING	DISPERSION (SQ MILES)
	X	Y
MEAN	15.95	232,063
MEDIAN	16	111,950

We chose the mean for our speed of onset ranking (*x*-values) in Table 3 to vertically separate disasters located in Quadrants I and II from Quadrants III and IV, as depicted in Figure 2. Using the mean also ensured that no disaster would fall on the divider between the quadrants. We chose the median for dispersion (*y*-values) to horizontally separate Quadrants II and IV from Quadrants I and III. We chose the median for dispersion because the mean yielded an uneven distribution of the disasters. This also provided a proportional split of the disasters between the localized and dispersed categories, again ensuring that no disaster would lie on the

separating value. This categorization resulted in 37 disasters placed in Quadrant I, 70 in Quadrant II, 97 in Quadrant III, and 64 in Quadrant IV.

Further analysis injected the third dimension of number of personnel affected, number of casualties, and total damage to each quadrant while we attempted to discover any connection to the complexity of relief operations during these disasters. We expected to find a significant factor separating the quadrants from one another based on the data contained in each.

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IV. DATA ANALYSIS

The review of literature suggested multiple contributors to the complexity of HADR operations. In the analysis conducted for this research, we strived to graphically represent this complexity in only two dimensions. Upon sorting our sample of disasters into their appropriate quadrants, we analyzed the additional defining characteristics of each disaster to identify any trends related to our research question.

A. INITIAL BREAKOUT OF LOCATION AND SPEED OF ONSET (*X* AND *Y* DATA)

As mentioned previously, when we initially plotted the *x* and *y* values, we noted two disasters that were significantly more dispersed than the others, which made the remaining disasters difficult to observe when graphed. After calculating *z*-scores for these two disasters, we further calculated *z*-scores for all of the disasters' *y* values and observed that these two disasters were the only disasters to have *z*-scores higher than 3 standard deviations from the mean. Removing these two disasters yielded a clearer picture of the dispersion of the disasters, represented in Figure 7.

Looking at our data represented in Figure 7, the most frequently reported (and assumed occurring) disasters were tropical cyclones (25), storms (24), forest fires (28), general floods (44), and tornados (57).

B. ADDITION OF THIRD VARIABLES

After graphing the *x* and *y* data, we wanted to compare each of these quadrants incorporating a third variable. The EM-DAT provided data for the number of personnel affected, number of casualties, and total damages incurred for each of our disasters, and we chose to incorporate each of these as a third variable. We assumed that as the value for each of these variables increased, so would the complexity of the disaster. This assumption enabled us to compare our data against the belief behind Figure 3.

These variables are introduced graphically and displayed in Figures 9 through 14. The third variables are reflected in each graph as a circle, with the size being proportionate to the other data points contained within the graph. The circles provide a good visual representation of how each disaster compares with others of similar type, dispersion, and speed of onset as well as highlight any additional outliers.

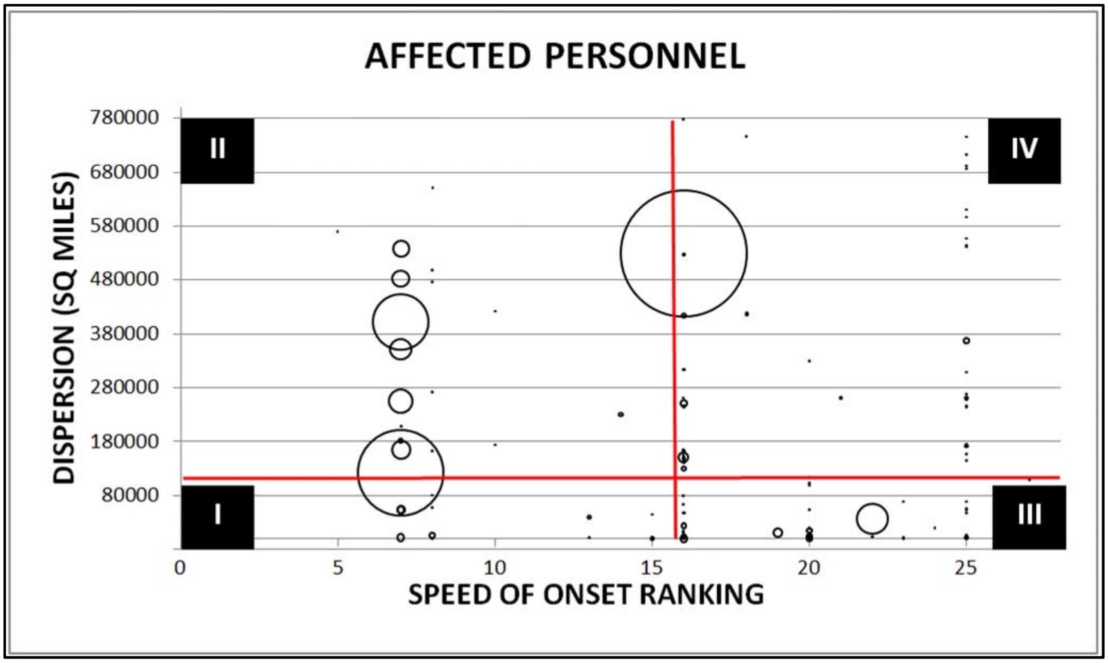

Figure 9. Plot of All Disasters With Number of Personnel Affected

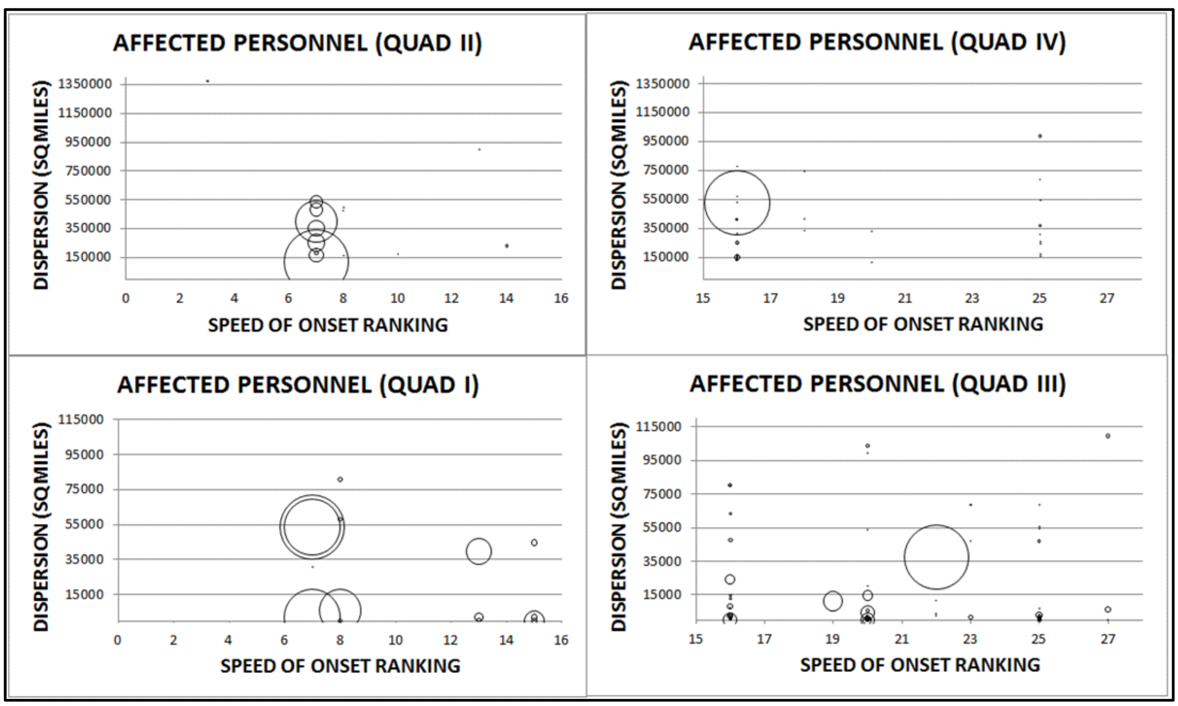

Figure 10. Plot of All Disasters With Number of Personnel Affected by Quadrant

Note. Circle Size is Relative Only to the Disasters in Each Respective Quadrant. Comparison Between Quadrants is Not Appropriate With This Figure.

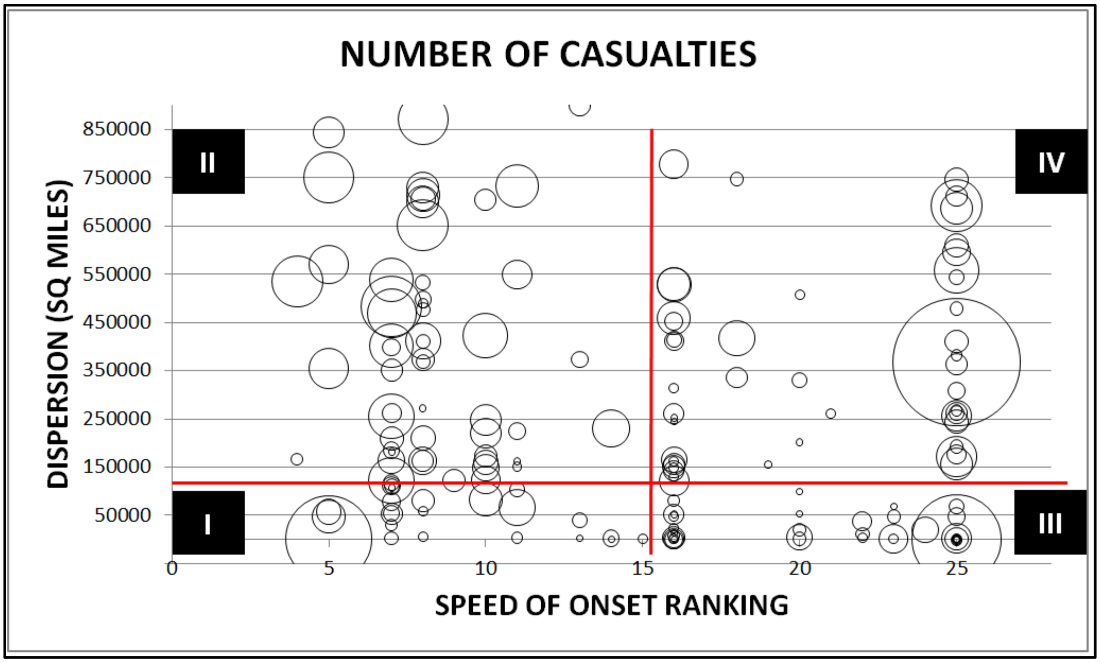

Figure 11. Plot of All Disasters With Number of Casualties

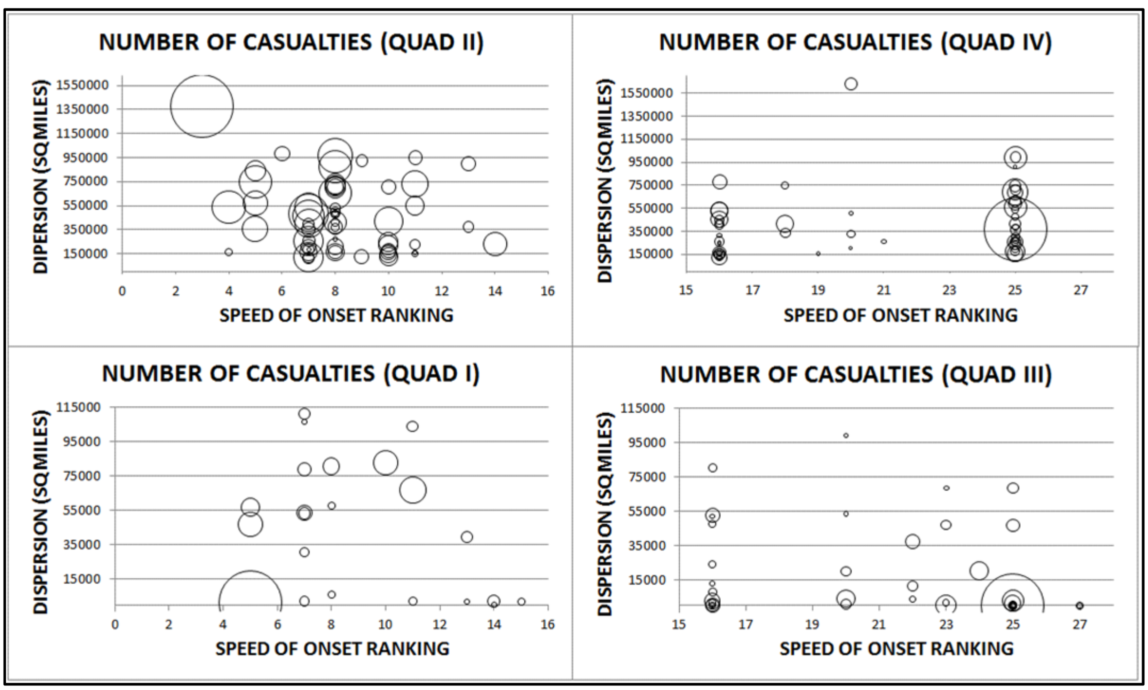

Figure 12. Plot of All Disasters With Number of Casualties by Quadrant

Note. Circle Size is Relative Only to the Disasters in Each Respective Quadrant. Comparison Between Quadrants is Not Appropriate With This Figure.

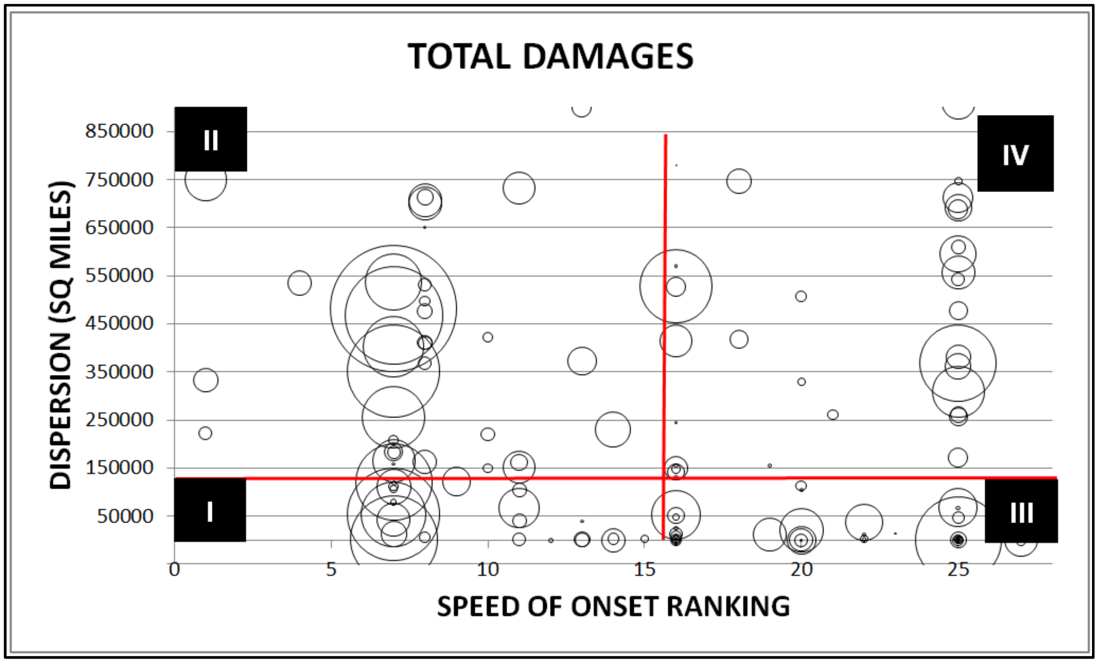

Figure 13. Plot of All Disasters With Total Damages

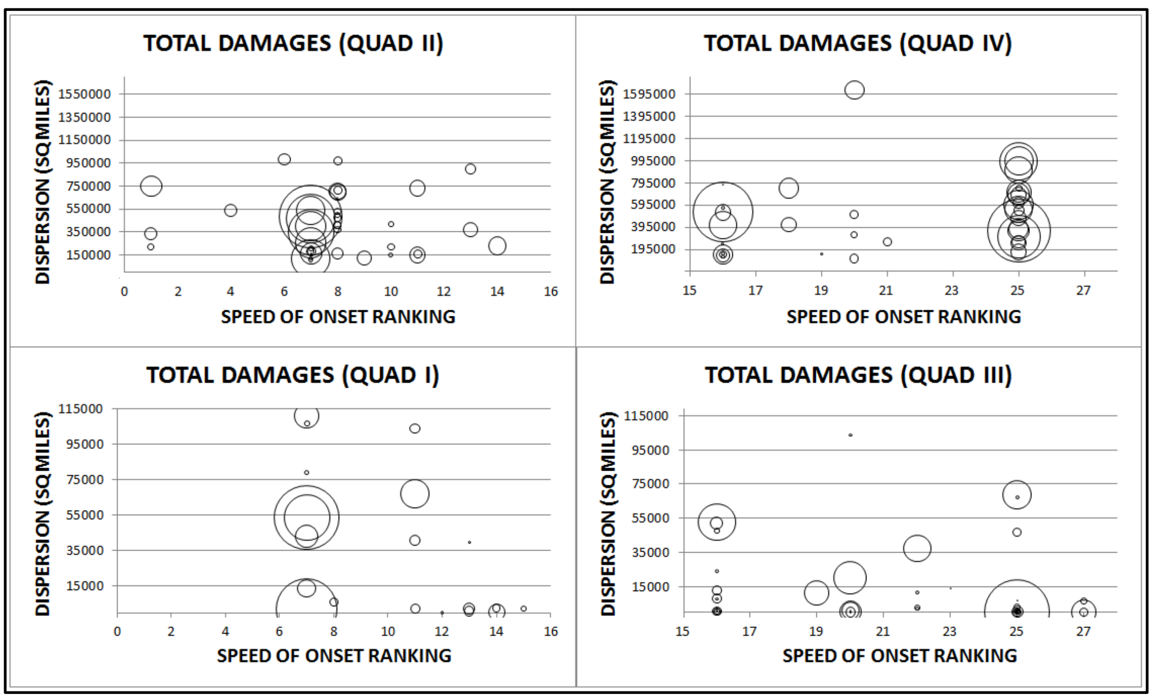

Figure 14. Plot of All Disasters With Total Damages by Quadrant

Note. Circle Size is Relative Only to the Disasters in Each Respective Quadrant. Comparison Between Quadrants is Not Appropriate With This Figure.

C. OUTLIERS WITHIN EACH QUADRANT

After incorporating each third variable and plotting the variables in graphs, we observed disasters that had significantly higher values for their respective third

variable. For example, Figures 9 and 10 each contain a circle that is significantly larger than their surrounding counterparts. This led us to believe that there were additional outliers in our data. We calculated the mean and standard deviation of each third variable, which enabled us to eliminate disasters with a *z*-score greater than 3. We repeated this process for Quadrants I through IV for each third variable, eliminating disasters from each quadrant that yielded a *z*-score greater than 3; the total count of outliers per quadrant are shown in Table 4. This process further reduced our disaster sample size from an initial 255 to 249 for number of personnel affected, 245 for number of casualties, and 238 for total damage.

Table 4. Count of Outliers Removed in Each Quadrant Per Variable

NUMBER OF OUTLIERS REMOVED PER QUADRANT BY VARIABLE				
DISPERSION	Four disasters removed from sample due to broad location data			
	QUAD I	QUAD II	QUAD III	QUAD IV
AFFECTED	1	2	1	2
CASUALTIES	2	2	4	2
DAMAGES	3	7	5	2

D. THIRD VARIABLE AVERAGES PER QUADRANT

After calculating *z*-scores for each third variable in each quadrant, we found that the outliers significantly affected all quadrants, but most significantly Quadrants II and IV for the number of personnel affected variable, changing the average personnel affected in Quadrant II from 123,469 to 19,635 and from 186,522 to 2,176 for Quadrant IV. Figures 15 through 17 allow for a visual comparison of quadrant averages before and after the outliers are removed.

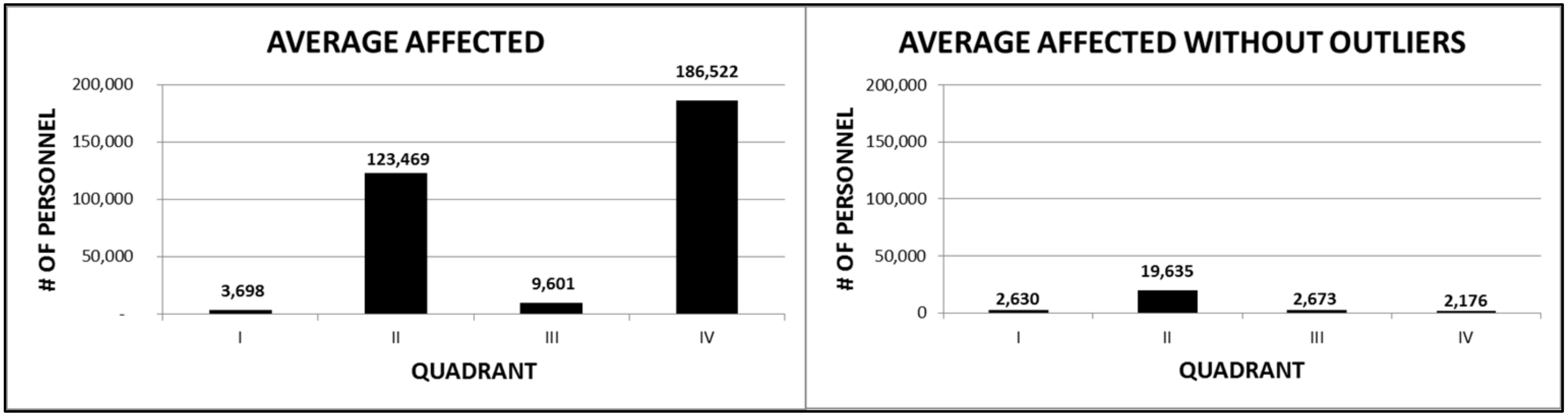

Figure 15. Average Number of Personnel Affected by Quadrant

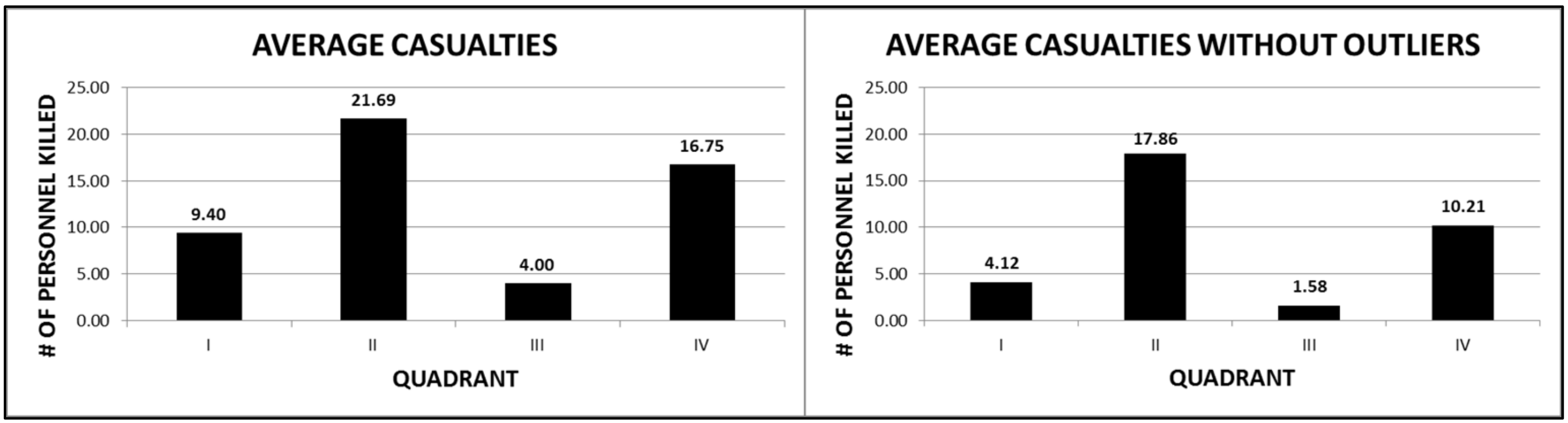

Figure 16. Average Number of Casualties by Quadrant

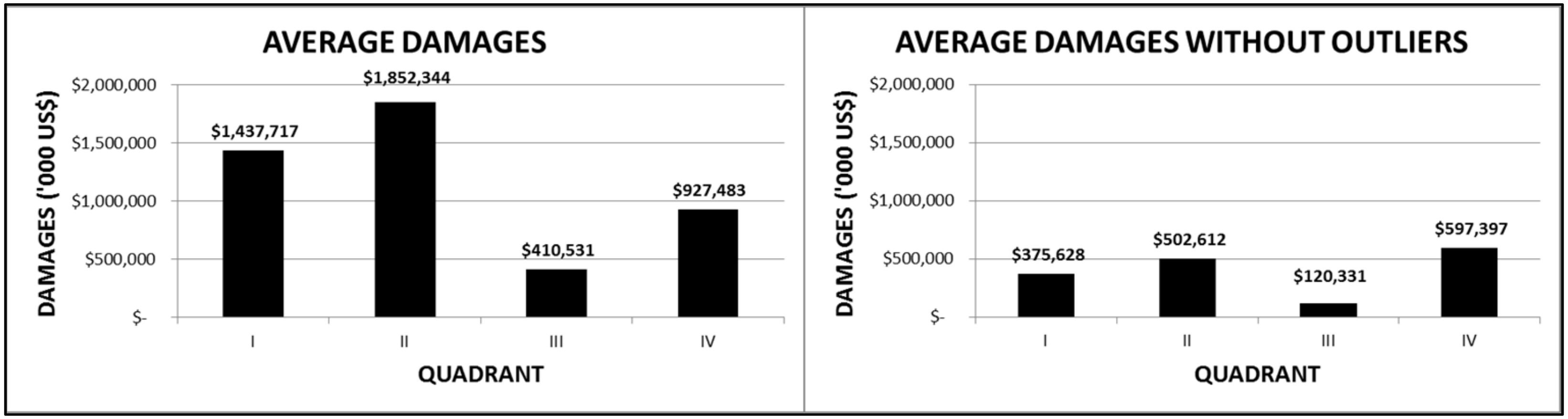

Figure 17. Average Damage (in Thousands US$) by Quadrant

E. THIRD VARIABLE DRIVERS BY QUADRANT

We found the percentages of each third variable by disaster type in each quadrant to determine which disaster types were noted as the drivers of complexity. The results are provided in Tables 5 through 7.

The data shows that hurricanes drive the number of personnel affected in Quadrants I and II while floods, mudslides, and tornados drive Quadrants III and IV. The number of casualties is driven by heat waves, hurricanes, and storms in Quadrants I and II and by floods and tornados in Quadrants III and IV. Finally, the total damages displayed a much wider spread: Quadrant I is driven by hurricanes and snowstorms/blizzards; Quadrant II by storms, droughts, and hurricanes; Quadrant III by earthquakes and forest fires; and Quadrant IV by tornados. Overall, hurricanes and tornados were observed to occur the most often, and their effects tended to cause the most damage and affect or claim the most lives.

Table 5. Sum of Total Personnel Affected by Disaster Type, Shown as Percentage of Quadrant Total

SUMMARY OF AFFECTED BY DISASTER TYPE, SHOWN AS PERCENT OF QUADRANT TOTAL									TOTAL DAMAGES	
	I		II		III		IV			
Speed of Onset Ranking	# of Occurrences	% of Quadrant Damages	# of Occurrences	% of Quadrant Damages	# of Occurrences	% of Quadrant Damages	# of Occurrences	% of Quadrant Damages	Total Occurrences	% of Total Damages
1	1	0.00%*	3	0.00%*					4	0.00%*
2									0	N/A**
3			2	0.27%					2	0.20%
4			2	0.00%*					2	0.00%*
5	3	0.00%*	4	0.00%*					7	0.00%*
6			1						1	0.00%*
7	8	67.11%	14	98.83%					22	76.41%
8	4	19.97%	20	0.18%					24	1.15%
9			2	0.00%*					2	0.00%*
10	2	0.00%*	8	0.02%					10	0.01%
11	5	0.00%*	7	0.00%*					12	0.00%*
12	1								1	0.00%*
13	3	7.95%	2	0.08%					5	0.46%
14	3		1	0.62%					4	0.46%
15	4	4.97%							4	0.25%
16					24	27.28%	18	54.77%	42	7.72%
17					1	0.00%*			1	0.00%*
18							3	3.16%	3	0.23%
19					1	22.62%	1	0.13%	2	3.15%
20					20	37.74%	8	2.92%	28	5.44%
21							1	1.03%	1	0.07%
22					5	0.24%			5	0.03%
23					5	1.00%			5	0.14%
24					1	0.01%			1	0.00%*
25					30	8.58%	27	37.99%	57	3.92%
26									0	N/A**
27					4	2.55%			4	0.35%
Grand Total	34	100.00%	66	100.00%	91	100.00%	58	100.00%	249	100.00%

* 0% is displayed due to total third variable value being 0 for the given disaster.

**No disasters of this type were included when analyzing this third variable.

Table 6. Sum of Total Casualties by Disaster Type, Shown as Percentage of Quadrant Total

SUMMARY OF CASUALTIES BY DISASTER TYPE, SHOWN AS PERCENT OF QUADRANT TOTAL									TOTAL DAMAGES	
	I		II		III		IV			
Speed of Onset Ranking	# of Occurrences	% of Quadrant Damages	# of Occurrences	% of Quadrant Damages	# of Occurrences	% of Quadrant Damages	# of Occurrences	% of Quadrant Damages	Total Occurrences	% of Total Damages
1	1	0.00%*	3	0.00%*					4	0.00%*
2									0	N/A**
3			1	0.00%*					1	0.00%*
4			2	2.98%					2	2.98%
5	2	1.86%	4	7.14%					6	8.99%
6			1	0.59%					1	0.59%
7	9	1.76%	15	14.76%					24	16.52%
8	4	0.73%	20	17.84%					24	18.57%
9			2	0.88%					2	0.88%
10	2	1.17%	8	7.43%					10	8.60%
11	4	0.39%	7	3.76%					11	4.15%
12	1	0.00%*							1	0.00%*
13	3	0.29%	2	0.78%					5	1.08%
14	3	0.34%	1	1.47%					4	1.81%
15	4	0.10%							4	0.10%
16					24	2.59%	20	9.53%	44	12.12%
17					1	0.00%*			1	0.00%*
18							3	2.00%	3	2.00%
19					1	0.00%	1	0.05%	2	0.05%
20					20	1.17%	8	1.08%	28	2.25%
21							1	0.10%	1	0.10%
22					6	0.68%			6	0.68%
23					4	0.34%			4	0.34%
24									0	N/A**
25					28	1.86%	25	16.18%	53	18.04%
26									0	N/A**
27					4	0.15%			4	0.15%
Grand Total	33	6.65%	66	0.576246	88	6.79%	58	28.93%	245	100.00%

* 0% is displayed due to total third variable value being 0 for the given disaster.
**No disasters of this type were included when analyzing this third variable.

Table 7. Sum of Total Damages by Disaster Type, Shown as Percentage of Quadrant Total

SUMMARY OF DAMAGES BY DISASTER TYPE, SHOWN AS PERCENT OF QUADRANT TOTAL									TOTAL DAMAGES	
	I		II		III		IV			
Speed of Onset Ranking	# of Occurrences	% of Quadrant Damages	# of Occurrences	% of Quadrant Damages	# of Occurrences	% of Quadrant Damages	# of Occurrences	% of Quadrant Damages	Total Occurrences	% of Total Damages
1	1	0.00%*	3	15.33%					4	5.35%
2									0	N/A**
3			2	0.00%*					2	0.00%*
4			2	3.59%					2	1.25%
5	3	0.00%*	4	0.00%*					7	0.00%*
6			1	3.26%					1	1.14%
7	6	46.53%	9	15.20%					15	11.68%
8	4	1.82%	20	26.29%					24	9.43%
9			2	4.89%					2	1.71%
10	2	0.00%*	8	2.25%					10	0.79%
11	5	33.44%	7	14.35%					12	9.59%
12	1	0.28%							1	0.04%
13	3	6.78%	2	7.18%					5	3.43%
14	3	10.32%	1	7.66%					4	4.09%
15	4	0.83%							4	0.11%
16					23	15.94%	19	12.86%	42	6.97%
17					1	0.00%*			1	0.00%*
18							3	4.91%	3	1.94%
19					1	19.10%	1	0.05%	2	2.30%
20					19	27.19%	8	4.33%	27	4.95%
21							1	0.53%	1	0.21%
22					5	1.43%			5	0.17%
23					5	0.05%			5	0.01%
24					1	0.00%*			1	0.00%
25					28	13.84%	26	77.33%	54	32.17%
26									0	N/A**
27					4	22.45%			4	2.68%
Grand Total	32	100.00%	61	100.00%	87	100.00%	58	100.00%	238	100.00%

* 0% is displayed due to total third variable value being 0 for the given disaster.

**No disasters of this type were included when analyzing this third variable.

F. EFFECTS OF OUTLIERS

Outliers are not always invalid data. They can simply highlight points that are significantly different than the rest of a sample. Several of the disasters in this sample appeared significantly different from most, yet they contained the most complete third variable data. It is important to note a few disasters that were considered outliers in this study. The two that stand out on the preceding affected personnel graph (Figure 9) are Hurricane Ivan, which struck the southeastern U.S. in 2004, displayed in Quadrant II, and the flood affecting eight states in the Midwest over 21 days during September 2008, displayed in Quadrant IV. Both of these disasters produced circles on the charts in Figure 9 that masked numerous other disasters in their respective quadrants.

We observed trends among our third variables when we compared them with our speed of onset ranking. Based on our ranking, Quadrant II carried the highest averages for all third variables, with Quadrant IV carrying the second highest. We found that the dispersion of the affected area has a greater impact on the complexity of the disaster than the speed of onset. Given the numerous disasters that contained only partial third variable data, these trends might have displayed a more linear trend—with Quadrant I yielding the lowest averages, Quadrants II and III being very similar, and Quadrant IV yielding the highest averages—had collection efforts been complete for every disaster in our sample. There appears to be a lack of documentation following the completion of relief efforts either due to agencies moving on to the next disaster or fundraising efforts to replenish expended resources. This lack of data impacts research intended to provide greater visibility in the HADR field.

V. CONCLUSION

Categorizing disasters based solely on their affected area and speed of onset does not provide a complete picture of the complexity of the relief operations required, although it does provide decision-makers with a soft generalization of how complex relief efforts might be, given a possible scenario. Our sample of disasters showed that the size of the affected area had a greater impact on the number of disasters that were placed in the more complex quadrants than speed of onset of disasters. Quadrants II and IV contained those disasters that held the highest values of affected personnel, casualties, and dollars of damage.

The analysis resulted in the belief that the number of personnel in the affected area, or population density of the affected area, is the greatest contributor to the complexity of relief operations. This analysis of the U.S. revealed that the biggest disaster culprits were tropical cyclones and tornados. The seasonality of these disasters provides areas that are typically affected with time to prepare before they occur, much more so with hurricanes than tornados. Regarding hurricanes, weather technology today can provide as much as a five-day lead-time before making landfall. As seen recently with Cyclone Phailin, which struck India, this lead-time can be utilized to prepare the disaster area by evacuating personnel before the disaster strikes. Evacuating personnel to safer areas helps to reduce the complexity immediately following a disaster occurrence because fewer limited resources are required to rescue survivors and collect casualties.

A method for measuring and identifying disasters based on their speed of onset is necessary to gain the full value of assigning disasters to specific quadrants, as shown in Figure 2. Although our method of assigning discreet variables provided a good visual representation, this method induced a biased guarantee that disasters would fall into one of the two quadrants on either side of the speed of onset ranking mean. Subsequent fallout from this method was highlighted by the averages of the third variables in each quadrant.

The lack of fidelity in measuring the affected area of the disasters in our sample allowed for self-induced error that may have significantly impacted the placement of several disasters. For smaller disasters, the affected areas tended to be more accurate because data provided was listed by city or county. With the larger disasters, especially in the category of "storms," we feel the error in our measurement of the affected area could be much greater. We observed that oftentimes the database listed multiple states as affected, but further analysis of historical weather maps showed it was only a portion of one state and the entire neighboring state that was affected. Collection efforts need to be more accurate to

benefit further analysis. It is imperative to also understand the context of those disasters that were identified as outliers in this analysis. Although the characteristics of those disasters showed that they were statistically different than the rest of the sample, they were actual occurrences. Referencing Table 4, the majority of the outliers would have been positioned in Quadrants II or III, representing those that either impacted a significant portion of land or occurred with a higher speed of onset. Decision-makers can prepare funding and response efforts for the "typical" results of disasters in each category but must be capable of supporting the larger scale disasters because they will strike.

A two-dimensional graph is the most simplistic picture to help visualize a set of data, but in this case, the story behind the graph may in fact provide more useful information. Although dispersion contributes to complexity more than the speed of onset, these variables are both uncontrollable. One key takeaway from our study is that time and evacuations are controllable variables that contribute the most to reducing the complexities of relief operations. The more people who are removed from the recovery portion of the immediate response phase, the less complex the operations will be. This provides relief agencies with time to focus on supporting the survivors and quickly begin the reconstruction phase. The lessons learned from past disasters are crucial to our societies' survival of future disasters. Further analysis of initial reports from Cyclone Phailin indicate that as few as 15 personnel have perished as a result of this storm. The state of Odisha was hit by a cyclone in 1999, when approximately 10,000 people lost their lives. A recent Reuters report by Gottipati and Dash (2013) stated that aid officials credited this minimization in loss of life to the population utilizing the many shelters built since 1999, the numerous evacuations, some of which were forced evacuations, and the five days' worth of warnings issued to residents. Weather tracking and predicting technology has improved tremendously in the last 15 years. When utilized and responded to properly, the time variable can help us gain a significant advantage in withstanding future natural disasters.

A. RECOMMENDATIONS

The following ideas will facilitate enhanced analysis of historical disasters to identify complexity drivers for the sake of improving the global community's preparation and response to future natural disasters. Developing a universal measurement for the speed of onset of disaster types will ensure proper disaster categorization. Accurate reporting of the affected area will improve the fidelity of analyzing the true impact of a given disaster. Detailed reporting of outcome variables by all involved agencies during post-mission wrap-up will significantly improve the capability of researchers to analyze characteristics that will ultimately define properties of each respective quadrant in Figure 2. Consider using population

density instead of using affected location because as the number of people to support increases, so does complexity.

B. FUTURE RESEARCH RECOMMENDATIONS

This research provided the foundation for determining whether a relationship exists between the complexity of relief operations based on the affected area and speed of onset of a natural disaster. Further research opportunities to advance this study are listed below. The HADR community must commit itself to improving data collection upon the completion of relief efforts to aid further research and advance the capabilities of response forces. If further research is conducted utilizing data from the CRED, researchers should be aware that we found that data fields within the database were not accurate, contained spelling errors, and/or were void of data. It was unclear if the absence of data meant that nothing occurred for that disaster (e.g., $0 of damage), or that the data was simply not collected for that variable. If the CRED is determined to be the resident collector of HADR statistics, then they must apply pressure to organizations involved with the recovery to ensure that data is submitted correctly and promptly. The CRED should also establish a working relationship with all major weather centers to validate and accurately define the locations affected by weather-related disasters. If the community will take ownership of the data collection required to facilitate further research, the bright minds of this community can begin developing methods to facilitate better planning and budgeting for future relief efforts.

1. Use Population Density to Define Affected Area

Utilizing the U.S. Census Bureau data, it is possible to calculate the population density of nearly all locations in the U.S. Since our analysis revealed an increase in the third variables as the affected area increased, it would be helpful to break it down further to determine if the population density was a greater driving force over the square mileage of the affected area.

2. Expand the Date Range to Include More Disasters

The database we utilized only contained disasters in a 10-year period. Expanding the date range will provide a larger sample for analysis and should refine the results, providing more accurate expected consequences of disasters in each quadrant. This will be limited by the same database inefficiencies that affected this research.

3. Expand the Research Boundaries to Include Global Disasters

Analyzing all global disasters would broaden the lens through which the disasters are viewed and provide a different perspective on number of personnel

affected, number of casualties, and total damages incurred. This analysis would require a more accurate and detailed database to obtain the best results.

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